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Car Travel Emissions Distribution in Germany

The Potential Impact of Electric Vehicles

Master Thesis

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Abstract

The push to transition passenger car fleets from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) has gained pace over the decade. While this transition is in progress, those who first adopt EVs will play a crucial role in deciding the extent of emissions reductions that can be achieved in the intervening years. To better comprehend the effect of EV adoption on emissions, attention needs to be paid to who should and who is adopting EVs, as well as to the complete environmental effect of EV use by considering the entire life cycle of the vehicles in question.

This thesis aims to explore the similarities and differences between those who travel and hence emit more and those who are more likely to adopt EVs and examine the potential emissions reductions that can be achieved through the adoption of EVs in the context of Germany. Data from the 2017 edition of the Mobilität in Deutschland (MiD) national travel survey of Germany was analysed using binary logistic regression to determine groups more likely to travel in excess, groups more likely to emit in excess, as well as groups more likely to adopt EVs. Variables such as gender and car ownership were generally significant in influencing excess travel, excess emissions as well as EV adoption. The results of this statistical analysis generally confirm the conclusions reached in established literature.

From the results of the statistical analysis, certain EV adoption scenarios were defined to illustrate the potential emissions reductions that can be achieved through the adoption of EVs by certain groups. These scenarios highlight the importance of prioritising certain groups when attempting to achieve sustainability goals through the reduction of emissions resulting from passenger car use.

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Transport accounted for a quarter of the European Union's (EU) total CO_2 emissions in 2019, 61% of which was attributed to passenger cars (European Parliament, 2023a). To achieve the climate goals set by the EU and to decarbonise the transport system, it will be vital to reduce or even eliminate the emissions generated from the use of passenger cars. In this vein, the EU Parliament has backed a ban on the sale of new petrol and diesel cars from 2035 onwards (European Parliament, 2023b). The introduction and adoption of electric vehicles (EVs) could provide a pathway to the reduction of CO_2 emissions from the transportation sector. This is especially relevant with EVs accounting for 42% of all newly registered passenger cars in Germany in 2021 (Kraftfahrt-Bundesamt, 2022). However, the manufacture of EVs and their batteries have been found to generate more CO_2 than the manufacture of internal combustion engine vehicles (Kawamoto et al., 2019). Additionally, this potential for CO_2 emissions reduction is heavily dependent on the electricity generation methods used to power EVs. Hence, such factors should also be taken into account when considering the potential CO_2 emission reduction resulting from the adoption of EVs.

The extent of EV adoption is not homogenous between different groups. Studies in Norway and Switzerland found battery electric vehicle adoption to increase with wealth income, education level, car sharing usage, and multicar households (Brückmann et al., 2020; Fevang et al., 2021). Travel behaviour such as trip purposes and the characteristics of such trips may also vary between different groups, resulting in varying travel mileages and emissions between the groups. Therefore, two research questions are proposed. The first correlates socio-economic groups and trip purposes to variations in travel distances and emissions using passenger cars. The second investigates whether the adoption of EVs in Germany lead to a reduction in CO_2 emissions from passenger cars.

A statistical analysis of the German national mobility survey, Mobilität in Deutschland, will be carried out to study the specific characteristics that point to differences in travel mileage and emissions resulting from said travel for car users in Germany. The adoption of EVs will be projected and the corresponding changes in emissions determined according to the EV adoption rates of different groups.

The student will present intermediate results to the mentors Joanna Ji (Research Associate, Associate Professorship of Travel Behavior, Technical University of Munich) in the fifth, tenth, 15th and 20th week.

The student must hold a 20-minute presentation with a subsequent discussion at the most two months after the submission of the thesis. The presentation will be considered in the final grade in cases where the thesis itself cannot be clearly evaluated.

Rolf Moeckel

Prof. Dr.-Ing. Rolf Moeckel

Student's signature

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

EU	European Union
ICEV	Internal combustion engine vehicle
EV	Electric vehicle
BLR	Binary logistic regression
LCA	Life cycle assessment
GHG	Greenhouse gas
GWP	Global warming potential
ICEP	Internal combustion engine – petrol
ICED	Internal combustion engine – diesel
ICEG	Internal combustion engine – gas
BEV	Battery electric vehicle
HEV	Hybrid electric vehicle
PHEV	Plug-in hybrid electric vehicle
MiD	Mobilität in Deutschland

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1. Introduction

The global movement to combat climate change and reduce the carbon footprint of human activity has gained momentum in the face of growing challenges posed by anthropogenic climate change. This necessitates the reduction or elimination of carbon emissions across all sectors of society. Energy supply and industry, which historically have been significant contributors to the carbon emissions of the European Union (EU), have seen declining emissions in recent years. In contrast, the transport sector in the EU has seen increases in emissions levels over the past decade (EEA, 2020). In fact, the transport sector alone accounted for a quarter of the EU's total CO_2 emissions in 2019, with passenger cars contributing 61% of transport-related emissions (European Parliament, 2023a).

This trend highlights a pressing need to curtail carbon emission in the transport sector, particularly from passenger cars in order to align with the EU's goal of achieving climate neutrality by 2050. To this end, EU legislation banning the sale of new petrol and diesel cars from 2035 onwards has already entered into force in April 2023 (European Parliament, 2023b). This phasing out of internal combustion engine vehicles (ICEVs), in conjunction with the introduction of electric vehicles (EVs) as a substitute is aimed at achieving a carbon neutral passenger car fleet. With an expected vehicle lifespan of 15 years, the timeframe defined for this transition is intended to ensure the elimination of ICEVs in the passenger car fleet of the EU by 2050. This is done with the hope that such policies would play a crucial role in ensuring that the transport sector in the EU can become carbon neutral by 2050.

The uptick in EV adoption in Germany can already be seen in data from the Kraftfahrt-Bundesamt, Germany's federal motor transport authority, where EVs comprised 42% and 49% of newly registered passenger cars in the 2021 and 2022 respectively (Kraftfahrt-Bundesamt, 2022). Therefore, at this critical juncture, it is vital to ensure that the transition from ICEVs to EVs would be effectively implemented such that the transport sector reduces its fair share of emissions.

1.1. Motivation

The adoption of EVs holds great potential in reducing passenger car carbon emissions, however this can be affected by a wide range of factors. One crucial aspect that should be considered is the heterogeneous nature of EV adoption within the general population. If only certain segments of the population, particularly those who travel the least, adopt EVs while others who travel extensively continue to rely on ICEVs, the overall reduction in carbon emissions resulting from the transition to EVs would be limited.

Hence, to maximise the environmental benefits of EV adoption, it is vital to identify the characteristics that point to both increased travel and thus greater emissions as well as a greater likelihood to adopt EVs. In the intervening years leading up to the target of climate neutrality in 2050, understanding exactly who adopts EVs first will play a crucial role in the extent of emissions reductions achieved during this period. Therefore, the identification of the characteristics affecting travel behaviour, namely travel mileage and emissions generated from this travel, as well as EV adoption likelihood would be able to aid in the development of strategies to target and incentivise EV adoption among segments of the population that contribute more to passenger car emissions.

Additionally, there are a range of factors affecting the extent to which carbon emissions can be reduced resulting from the adoption of EVs. These include the emissions generated by the respective vehicles over their lifespans and the carbon intensity of the electricity used to power the newly adopted EVs. Consequently, the overall emissions of an EV may be equal to or even greater than that of an ICEV (Kawamoto et al., 2019). Therefore, a comprehensive assessment of the potential impact of the EV transition on passenger car emissions must consider various factors. These include the travel behaviour and EV adoption patterns of different segments of the population as well as the total emissions generated over the entire lifecycle of the vehicles in question. Only by accounting for these factors can the effective change in carbon emissions resulting from the transition of the passenger car fleet from ICEVs to EVs be determined.

This thesis aims to contribute to the existing discussion on the adoption of EVs and their effects by examining the relationship between travel behaviour and EV adoption to determine key factors influencing the transition to EVs. Through this analysis, segments of the population that should be targeted for sustainable mobility initiatives can be pinpointed. At the same time, more effective measures for reducing carbon emissions resulting from passenger car use in Germany can be implemented. Moreover, the potential for carbon emissions reductions from the transition to EVs can be evaluated from the identified population segments. This paves the way to a better understanding of the extent of emissions reductions that can be achieved from the adoption of EVs by the respective population segments. From this, measures that maximise emissions reductions from can be formulated.

1.2. Objectives and scope

The two objectives of this thesis are to:

1. Explore similarities and differences between excess groups and groups more likely to adopt EVs
2. Investigate whether the adoption of EVs in Germany would lead to reduced carbon emissions

As this thesis aims solely to determine the effect of EV adoption on carbon emissions, it is assumed that the patterns in travel behaviour reflected in the current population would persist in the future projections. Additionally, the population size and any changes to it is also not considered in this thesis, with potential emissions reductions calculated on a per person basis. Lastly, this thesis focuses solely on the adoption of EVs in the passenger car fleet and no other forms of vehicles.

1.3. Organisation of the thesis

This thesis report is organised as follows. Chapter 2 of this thesis covers current relevant background literature. Chapter 3 discusses the data and methods used in this thesis. Chapter 4 presents the results of the statistical analysis while Chapter 5 explores the effects of EV adoption. Finally, Chapter 6 discusses the limitations and recommendations for further work and provides a conclusion for this thesis report.

2. Literature review

2.1. Travel behaviour and emissions analysis

Many studies have been undertaken to analyse the dynamics of travel mileage and emissions distributions and the factors that influence said distributions. This is generally accomplished through the analysis of survey data, particularly household travel surveys. These surveys, through the record of travel data as well as socio-demographic data enables the identification of individuals or groups in the population who travel and emit beyond the average. These groups are commonly referred to as excess groups, reflecting their travel or emissions patterns that significantly differs from the average.

This topic has been extensively studied in the United Kingdom drawing from a wide range of data sources. Using multivariate regression on data collected through a survey in Oxfordshire to determine characteristics affecting excess travel, Brand and Preston (2010) found that the top quintile of travellers contributes to 60% of total emissions generated by the surveyed population. A similar conclusion was drawn by Brand et al. (2013) which used linear and binary logistic regression (BLR) on data obtained from a survey of Cardiff, Kenilworth, and Southampton to study predictors of transport-related carbon emissions. Through their analysis, they found the top quintile to be responsible for 65% of car travel emissions in contrast to 0.2% by the bottom quintile.

Elsewhere, in their study of Seoul, South Korea, Ko et al. (2011) examined the socio-economic characteristics of the top 10% of emitters using data from the 2006 household travel survey. They further used a tree-based regression model to determine likely characteristics as well as a threshold for defining high emitters in Seoul. They then developed a binary logistic model to investigate the probabilities of being a high emitter based on their identified socio-economic characteristics. Additionally, they found the top 10% of emitters in be responsible for 63% of transport-related emissions. Meanwhile, in the context of Germany, Reichert et al. (2016) studied the impact that social and spatial factors had on long-distance trips using logit and ordinary least square regressions. Comparisons were then made against the impacts that these same factors had on daily travel and their associated emissions. Their research established that while both long-distance trips and daily trips were similarly affected by socio-demographic characteristics, the same could not be said for spatial attributes such as municipality size.

Some studies also aim to identify characteristics pointing to excess travel in addition to excess emissions. This is because the relations between the characteristics and each of these two groups may not be the same. A myriad of factors ranging from the vehicles that are driven to the occupancy rate of the vehicles when making certain trips. In their study based on the National Travel Survey in England, Wadud et al. (2022) used BLR to find characteristics indicating excess travel or excess emissions. By defining high and excess travel and emitter groups as the top 20% and top 5%, this allowed them to also study the differences between emission groups as well as between excess travellers and excess emitters. Through this, they found that targeting the top 20% of users instead of only the excess group with a mileage rationing scheme could reduce emissions by 26%.

Therefore, the study of travel behaviour and emissions needs to consider the differences between long-distance and daily trips, as well as possible differences between those who travel more and those who emit more. Table 1 summarises the recurring variables found to be significant in predicting excess travel or emissions in the studies reviewed.

Table 1: Significant variables affecting excess travel and emissions

Author/s (Year)	**Variables**								
	Gender	Age	Employment	Ethnic background	Household structure	Household income	Educational attainment	Residential location	Car ownership
Brand and Preston (2010)	X	X	X	-	-	X	-	-	X
Brand et al. (2013)	X	X	X	X	-	X	X	-	X
Buchs and Schnepf (2013)	X	X	X	-	X	X	X	X	-
Ko et al. (2011)	X	X	X	-	-	X	-	-	X
Reichert et al. (2016)	X	-	X	-	X	X	X	-	X
Wadud et al. (2022)	X	X	X	X	X	X	X	X	X

While the studies above explored a wide array of factors affecting the likelihood of excess travel or emissions, several recurring patterns were observed. One consistent trend observed across these studies was that males, those of working age, those who were employed full-time, and those earning a higher household income were seen to exhibit a greater propensity to travel or emit more than the average. Additionally, higher levels of education, the presence of children in the household and the ownership of multiple cars within a household were frequently identified to be significant characteristics associated with an increased likelihood of excess travel or emissions. Moreover, Wadud et al. (2022) observed that single adult households were twice as likely to be excess emitters but no more likely to be excess travellers. This was attributed to single individuals being unable to share trip-based activities while also having lower vehicle occupancy rates. Lastly, a couple of studies found non-whites and those who lived in rural regions to be more likely to travel or emit in excess compared to the average.

The variables listed above formed the basis for the selection of variables for the analysis carried out in this thesis as they have been demonstrated to be relevant in the determination of excess travel and emissions. Additionally, the conclusions drawn from the observations of these studies also provide insight into the expected relationship between the characteristics studied in this thesis and excess travel and emissions.

2.2. Vehicle emissions

The increase in the proliferation of EVs in recent years has provided impetus to the detailed study of the environmental impacts of EVs. When comparing the environmental impact of EVs against that of ICEVs, many factors need to be taken into account, including the production and disposal of these vehicles before and after they are used. While it is generally accepted that EVs produce fewer emissions compared to ICEVs during their operation, the manufacture of EVs can result in a larger overall carbon footprint than that of ICEVs. This is largely due to the resource-intensive production of batteries and electrical components that EVs require, which are not used in ICEVs. Additionally, the disposal of these batteries and components also results in carbon emissions that are not produced or are produced in smaller amounts when disposing ICEVs.

Therefore, life cycle assessments (LCAs), which assess the environmental impacts across all the life stages of a product, should be utilised when assessing the impact of the transition to EVs on carbon emissions from passenger car use. To allow for comparisons across different vehicles and studies, emission factors are used. Emission factors represent the specific amount of emissions generated per unit of activity. In the context of vehicle LCAs, the total amount of emissions produced by a vehicle is generally measured in gCO_2/km (grams of carbon dioxide per kilometre), this is the total amount of emissions produced by a vehicle over its lifespan divided by the total lifespan mileage of said vehicle.

All the studies reviewed utilised the carbon dioxide equivalent (CO_2eq) when evaluating the climate impact of the vehicles over the course of their lifespans. The use of this measure meant that other greenhouse gases (GHGs) that may be produced can be converted to an equivalent of CO_2. This allowed for the consideration of the impact of all GHGs produced, producing results that more accurately reflect the total climate impact of the vehicles in question. Additionally, many of the studies reviewed considered the global warming potential (GWP) of the GHGs released. This measure considers the total climate effect that the respective GHGs have over a set period relative to CO_2. This produces a more comprehensive picture of the climate effect of

GHGs as different GHGs have different heating effects and leave the atmosphere at different speeds. The most used GWP in the studies reviewed was GWP20, the total climate effects of the GHGs relative to CO_2 over a course of 20 years.

The emission factors for passenger cars can be affected by a wide range of factors. Most significant of these is the overall lifetime mileage of the vehicle being studied. While this directly affects the overall emissions produced by a vehicle over its lifetime, this is accounted for using the unit g/km when using LCAs to evaluate the emission factors of vehicles. However, a higher lifetime mileage causes the emissions produced during the non-operation phases to be distributed over a longer lifespan, reducing the emissions generated per kilometre travelled. Moreover, when considering EVs, the possible need for battery replacement during the lifespan of a vehicle also needs to be considered. This is due to the limited lifespan of the batteries used by EVs as the condition of such batteries deteriorate over time after numerous charging and discharging cycles. Hence, studies that consider higher lifetime mileages of vehicles could necessitate a battery replacement for the EVs being evaluated. This would result in greater emissions due to the environmental impact of manufacturing replacement batteries. For example, Kawamoto et al. (2019) found that battery electric vehicles (BEVs) generally produced more emissions than ICEVs if driven for more than 160,000 km due to the emissions generated from the manufacture of a replacement battery. This is because the manufacture of batteries constitutes a significant proportion of the lifetime carbon emissions generated by EVs.

Moreover, the extent of emissions reduction that can be achieved by the transition from ICEVs to EVs strongly depends on the country or region being studied. This is due to the differing carbon intensity of the electricity used to power EVs, which refers to the amount of emissions produced for each unit of electricity generated. EV use in places where the power mix is cleaner or more efficient would therefore generate less emissions than in places where fuel sources such as coal are used for power generation. For example, Kawamoto et al. (2019) found the carbon intensity of electricity to be dominant in determining the points where the lifetime emissions of EVs and ICEVs intersect. At the same time, carbon emissions per unit of electricity generated are generally projected to decline over time. This is a consequence of expected technological advances improving the efficiency of power generation, transmission, and distribution. A parallel shift in overall power mixes towards cleaner or renewable sources of energy such as solar and wind power is also expected to gradually reduce the carbon footprint of the electricity used to power EVs over time.

Therefore, the various LCAs of vehicles can produce a wide range of emission factors resulting from the variations in the parameters that they consider and define. The studies considered in this thesis and their respective parameters, as well as the vehicle fuel types considered in each study are provided in Table 2 below. The ICEVs studied are split into the following three categories: internal combustion engine – petrol (ICEP), internal combustion engine – diesel (ICED), internal combustion engine – gas (ICEG). Similarly, the EVs studied are also split into three categories: BEVs powered solely by electric batteries, hybrid electric vehicles (HEVs) powered solely by combustion engines and cannot be charged by external sources, and plug-in hybrid electric vehicles (PHEVs) that are like HEVs but possess bigger batteries that can be charged by external sources. Furthermore, a plot of the emission factors obtained from the studies reviewed in this thesis is provided in Figure 1 below, with the respective article numbers denoting which study each point is derived from. A detailed description on the application of the results from the LCA studies reviewed in this thesis are further discussed in the second half of Chapter 3.

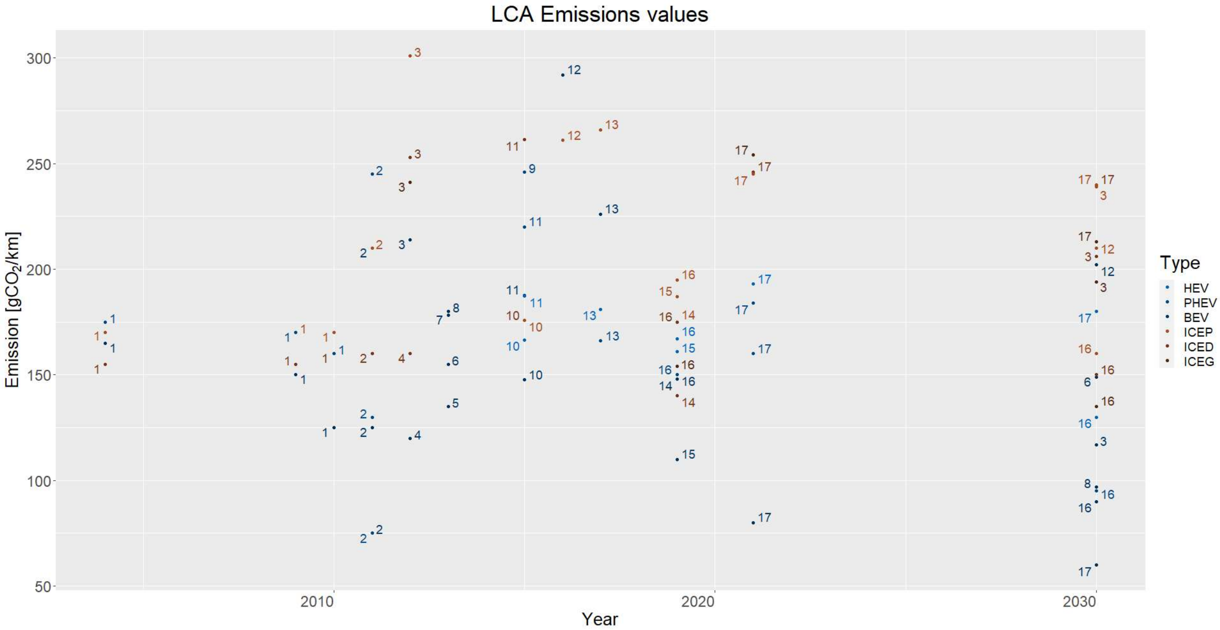

Figure 1: Emission factors of vehicles in all LCAs reviewed

As seen in Figure 1 above, a wide range of emission factors were calculated for the emissions factors by the different LCA studies. Nonetheless, it can be observed that these studies generally concluded that after accounting for all stages over a vehicle's lifetime, EVs still generated less emissions than ICEVs. Another observed trend that was evident was the reduction of emissions values over time, regardless of the fuel type in question. It was also noted that the year 2030 was chosen as a future prediction year across all the studies reviewed.

Table 2: Parameters of LCA studies reviewed

Art. no.	Author/s (Year)	Country	Year(s) studied	ICEP	ICED	ICEG	BEV	HEV	PHEV	Lifetime mileage [km]	Lifespan [years]	Battery change (EV) [km]
1	Freire and Marques (2012)	Portugal	2004, 2009, 2010	X	X	-	X	-	X	200,000	10	Yes
2	Faria et al. (2013)	-	2011	X	X	-	X	-	X	-	-	No
3	Bauer et al. (2015)	-	2012, 2030	X	X	X	X	-	-	240,000	-	150,000
4	Tagliaferri et al. (2016)	EU	2012	-	X	-	X	-	-	150,000	-	No
5	Koroma et al. (2022)	-	2013	-	-	-	X	-	-	160,000	12	No
6	Girardi et al. (2015)	Italy	2013, 2030	-	-	-	X	-	-	150,000	-	No
7	Bartolozzi et al. (2013)	Italy	2013	-	-	-	X	-	-	200	-	-
8	Helmers et al. (2015)	Germany	2013, 2030	-	-	-	X	-	-	100,000	-	-
9	Crossin and Doherty (2016)	Australia	2015	-	-	-		-	X	255,000	15	-
10	Ma et al. (2012)	UK	2015	X	X	-	X	X	-	180,000	15	-
11	Onat et al. (2015)	USA	2015	X	-	-	X	X	X	240,000	-	-
12	Bohnes et al. (2017)	Denmark	2016	X	X	-	X	X	-	150,000	-	100,000
13	Lombardi et al. (2017)	-	2017	X	-	-	X	X	X	200,000	10	Yes
14	Kawamoto et al. (2019)	EU	2019	X	X	-	X	-	-	200,000	-	160,000
15	Pipitone et al. (2021)	EU	2019	X	-	-	X	X	-	150,000	11.5	No
16	Ternel et al. (2021)	France	2019, 2030	X	X	X	X	X	X	150,000	10	No
17	Bieker (2021)	EU	2021, 2030	X	X	X	X	X	X	243,000	-	No

2.3. EV adoption

With the proliferation of EVs and their expected role of largely substituting ICEVs, especially in EU passenger car fleets, many studies exploring the adoption of EVs have been carried out. While some focus on the possible changes to fleet composition and their effects, some studies aim to determine specific characteristics that indicate increased likelihood to adopt EVs or the underlying reasons for EV adoption. These studies employ a wide arrange of methodologies such as surveys, simulations, sales analysis, and expert interviews to investigate the dynamics of EV adoption. An overview of the factors that were found to be significant in the adoption of EVs is provided in Table 3 below.

For many of the factors listed, majority of the studies drew the same conclusions although the studies were carried out in various countries. EV adopters or likely adopters tend to have the following characteristics:

- Male
- Prior experience with EVs
- Greater environmental awareness
- Middle to high household income
- Highly educated
- Employed full-time or in technical professions
- Homeowner
- Increased car ownership
- Living in larger households or households with children

However, when looking at age and home locations, there were conflicting conclusions drawn by the studies reviewed in this thesis. While many found that middle aged people were more likely to adopt EVs, some instead concluded that younger individuals were more likely to adopt EVs. Similarly, there was disagreement on whether urban or metropolitan users were more likely to adopt EVs compared to rural or suburban users. The variables listed in Table 3, similar to those in Table 1, served as the basis for variable selection in the analysis carried out in this thesis.

Table 3: Variables affecting EV adoption

Author/s (Year)	Variable										
	Gender	Age	Experience	Environmental awareness	Income	Education	Employment status	Home ownership	Vehicle ownership	Household structure	Home location	Long distance commuters
Ahmadi et al. (2015)	X	-	-	-	-	-	-	-	-	-	-	-
Axsen et al. (2016)	X	X	-	-	X	X	-	X	-	-	-	-
Barth et al. (2016)	X	X	X	-	X	-	-	-	-	-	-	-
Bruckmann and Willibald (2020)	-	-	-	-	-	-	-	X	-	-	-	-
Carley et al. (2013)	X	X	X	X	-	X	-	-	-	-	-	-
Chen et al. (2020)	X	X	X	-	X	-	-	-	X	X	-	-
Ferguson et al. (2018)	-	X	-	-	-	X	-	-	-	-	X	-
Fevang et al. (2021)	-	-	-	-	X	X	-	-	-	-	-	-
Figenbaum and Kolbenstvedt (2016)	-	X	-	-	-	-	-	-	X	X	-	X
Hackbarth and Madlener (2013)	-	X	-	X	-	X	-	-	-	-	-	-
Javid and Nejat (2017)	-	-	-	-	X	X	-	-	-	-	-	-
Ling et al. (2021)	X	-	X	-	X	-	-	-	-	-	-	-
Mukherjee and Ryan (2020)	-	X	-	-	-	X	-	X	-	-	-	X
Musti and Kockelman (2011)	-	-	-	-	-	-	-	-	X	-	-	-
National Platform Future of Mobility (2021)	-	-	X	-	-	-	-	-	-	-	-	-
Nayum et al. (2016)	-	X	-	-	X	X	X	-	-	X	-	-
Peters and Dutschke (2014)	X	X	-	-	-	-	X	-	X	X	X	-
Plötz et al. (2014)	-	X	-	-	-	-	X	-	-	X	X	-
Priessner et al. (2018)	X	-	-	-	-	-	-	-	X	X	-	-
Simsekoglu and Nayum (2019)	X	-	-	-	-	-	-	-	-	-	-	-
Tal & Nicholas (2013)	-	-	-	-	X	X	-	-	-	-	-	-
Vassileva and Campillo (2017)	-	X	-	-	X	X	-	-	-	-	-	-
Wappelhorst et al. (2022)	-	-	-	X	-	-	-	-	-	-	-	-
Westin et al. (2018)	-	X	-	-	X	X	-	-	-	-	X	-
Zarazua de Rubens (2019)	X	X	-	-	X	X	-	-	-	-	-	-

3. Material and Methods

3.1. Data description

To identify patterns in the travel behaviour of the German populace and the characteristics associated these patterns, a statistical analysis was carried out on the results of the German household travel survey, Mobilität in Deutschland (MiD). This thesis utilises data from the 2017 edition of the MiD survey, henceforth referred to as MiD2017, in its analysis. This survey covers households throughout Germany and records their socio-demographic information as well as their daily travel behaviour. The survey was carried out in two phases. The first phase involved the execution of a household survey to record mainly household related information such as the household composition and available transport means of respondents. The second phase was then carried out to record personal characteristics of household members as well as the trips that they made on a single study date. MiD2017 was carried out over a survey period of more than 12 months, from May 2016 to September 2017, MiD2017 sampled a total of 156,420 households, accounting for 316,361 persons making a total of 960,619 trips on their surveyed dates.

The data obtained from this survey was then split into six datasets: households, persons, trips, vehicles, travel, and stages. In this thesis, no data from the travel and the stages datasets were used. The travel dataset comprised overnight trips that were made by respondents in the three months leading up to their surveyed dates, which was not of interest in the context of this thesis. Meanwhile, data from the stages dataset was not used in this thesis because only a small proportion of the recorded responses included this information on every stage of the trips that were made. Travel patterns and their resulting emissions were investigated using data available in the trips and vehicles datasets. Meanwhile, socio-demographic data of the individuals whose travel behaviour were investigated was obtained from the households and persons datasets. More details on these applications of the survey are provided at the end of this chapter.

3.2. Data preparation

Before the analysis for this thesis could be carried out, the data provided from MiD2017 was prepared through the following steps. Firstly, the trips data was processed into a format suitable for joining socio-demographic data. The scope of this thesis that only considers passenger car use meant that only trips that were carried out by car, whether as a driver or a passenger, were considered. Hence, only trips which reported passenger cars as the main mode used were taken. As Wadud et al. (2022) found in the analysis of data from the English equivalent of MiD2017, there were differences in the characteristics that were found to affect excess travel as compared to that of excess emissions. Hence, this thesis considered both in its analysis of the travel behaviour of the German populace. The formula for calculating the emissions generated for each trip is shown in Equation (1) below.

$$Emissions\ [kg] = \frac{Trip\ length\ [km] \times\ Emissions\ factor\ \left[\frac{kg}{km}\right]}{Number\ of\ persons} \tag{1}$$

To be able to calculate the corresponding emissions generated from each trip that was made, the above variables had to be known or determined. The emissions factor is based on the respective fuel types of the cars used in making the recorded trips. However, approximately 90% of the trips travelled by car that were recorded in the survey did not have data as to the exact vehicle used during the trip. Consequently, the average car owned by each respective household was used to calculate the emissions generated in these trips. This was accomplished using data from the vehicles dataset, where information on the cars owned by every household was recorded. Therefore, only trips where the trip length, the vehicle used, and the number of persons travelling on that trip were known were included in the processed dataset. The data was then reorganised into a person-based dataset where every entry represented one person. The total distance travelled and resulting emissions generated for each person were also calculated and included for further analysis into the possible reasons for variations in travel behaviour between excess groups and the average person.

Reichert et al. (2016) determined that while socio-demographic factors affected both daily trips and long-distance travel in the same direction, the extent of their effects were not the same. Hence, this thesis also considers possible differences between the factors affecting these two types of travel. Consequently, two dataset variants were created to be analysed, one containing every trip that was reported, and another filtered for only trips there were below 100 km each. These are henceforth referred to as “all trips” and “daily trips” respectively. A threshold of 100 km per trip was selected as it was the generally used value to define long-distance trips in research conducted in the EU.

With the travel-related data prepared and reorganised, socio-demographic data from the person and household datasets were processed and joined to the person-based datasets. As stated in Chapter 2, variables found to be significant in affecting travel behaviour as well as EV adoption likelihood served as the basis of variable selection for the analysis carried out in this thesis. Some variables highlighted by existing literature such as ethnic background or environmental awareness were not recorded in MiD2017 and hence could not be included. The inclusion of variables such as migration background and frequency of usage of different transport modes that were not measured in previous studies was attempted but such variables were ultimately not included since over 25% of responses were invalid, meaning no answer was given for these survey questions. Lastly, some variables were amended to improve comparability across different households or individuals as well as to reduce redundancies in the variables studied in this thesis. For example, the ownership of different vehicle types and the annual car mileage of households were normalised according to the respective weighted household sizes to compensate for differing household sizes and structures. This is because the weighted household size considers the age of household members, with the first adult counting as 1 and every additional adult and child (those above 14) counted as 0.5 and 0.3 respectively. Additionally, the categories of certain variables such as age groups were merged to reduce the complexity of the analysis and to create more meaningful categories.

To better understand the relationship and eliminate redundancies between the characteristics being studied, correlation tests were carried out between the analysed characteristics. In this check, some variables were found to show a strong correlation with other variables, resulting in the elimination of these variables. Only persons with valid responses for all the socio-demographic variables considered in this study were included in the datasets, this was done to ensure the accuracy of the analysis carried out. A comparison of the number of persons and trips made between the original data and the processed datasets are provided in Table 4 below. The final list of variables, with their original as well as translated and processed labels and categories are provided in Table 5 below. The processed socio-demographic data was then joined to the respective persons in the person-based trip datasets.

Table 4: Comparison of person and trip numbers across datasets

	MiD2017 data	**Car users**	**All trips**	**Daily trips**
Persons	960,619	509,874	359,756	351,598
Trips	316,361	163,667	121,426	118,265

Table 5: Original and processed variable labels and categories

Original variable labels and categories	Translated and processed variable labels and categories
Wohnen zur Miete oder Eigentum Miete Eigentum Anderes	**Home ownership status** Renting Homeowning
Anzahl Autos im HH 0-30	**Household car ownership** <1 1+
Anzahl Motorräder/Mopeds/Mofas im HH 0-30	**Household motorbike ownership** <1 1+
Anzahl Fahrräder im HH 0-30	**Household bike ownership** <1 1+
Anzahl Pkw-Führerscheinbesitzer(innen) im HH 0-15	**Household driving licence ownership** <1 1+
gewichtete Haushaltsgröße nach neuer OECD-skala 1-4,5	**Weighted household size** 1 person Up to 1.5 persons Less than 2 persons 2+ persons
ökonomischer Status des Haushalts sehr niedrig niedrig mittel hoch sehr hoch	**Economic status of household** Very low Low Medium High Very high
Haushaltstyp: Differenzierung nach Größe, Alter und Kindern 1-Personen-HH: Person 18-29 Jahre 1-Personen-HH: Person 30-59 Jahre 1-Personen-HH: Person 50 Jahre und älter 2-Personen-HH: jüngste Person 18-29 Jahre 2-Personen-HH: jüngste Person 30-59 Jahre 2-Personen-HH: jüngste Person 60 Jahre und älter HH mit mind. 3 Erwachsenen HH mit mind.einem Kind unter 6 Jahren HH mit mind.einem Kind unter 14 Jahren HH mit mind.einem Kind unter 18 Jahren Alleinerziehende(r)	**Household with minors (below 18 years of age)** All adult household Minor in household
höchstes Segment der Autos im HH (nach KBA) klein kompakt mittel groß	**Highest car segment in household** Small Compact Medium Large
Geschlecht männlich weiblich	**Gender** Male Female
Altersgruppen 0-5 Jahre 6-9 Jahre 10-13 Jahre 14-17 Jahre 18-24 Jahre 25-44 Jahre 45-59 Jahre 60-64 Jahre 65 Jahre und älter	**Age group** 0-17 18-24 25-59 60+

Umfang Berufstätigkeit Vollzeit berufstätig Teilzeit berufstätig, d.h. 18 bis unter 35 Stunden pro Woche geringfügig berufstätig, d.h. 11 bis unter 18 Stunden pro Woche berufstätig als Nebentätigkeit oder im Praktikum berufstätig ohne Angabe zum Umfang Auszubildende(r) nicht berufstätig	**Employment status** Full-time employed Part-time employed, 18-34 hours/week Marginally employed, 11-17 hours/week Part-time job/Internship Employed (unspecified) Apprenticeship Not working
Person hat einen Nebenwohsitz ja nein	**Secondary residence** Yes No
Bildungsabschluss (noch) kein Abschluss Volks- oder Hauptschule, POS 8. Klasse mittlere Reife, Realschulabschluss, POS 10. Klasse Fachhochschulreife, Abitur, EOS 12. Klasse bzw. Berufsausbildung mit Abitur Fachhochschul- oder Universitätsabschluss anderer Abschluss	**Level of education** No degree (yet) Elementary or secondary school Secondary school leaving certificate Technical college entrance qualification, Abitur College or university degree Other degree
Regionalstatistischer Regionstyp Stadtregion Ländliche region	**Regional statistical region type** Urban Rural
Hauptzweck des Weges Arbeit Dienstlich Ausbildung Einkauf Erledigung Freizeit Begleitung	**Trip purpose** Commuting Business Maintenance Leisure Accompaniment

3.3 Statistical analysis

As Wadud et al. (2022) found in their analysis of the English equivalent of MiD, the role that the respective characteristics play on excess travel differs from that of excess emissions. This was taken into consideration in the approach of this thesis, investigating the of the characteristics studied on excess travel as well as emissions. Additionally, two groups of excess users were defined for excess travel and excess emissions each, resulting in a total of eight excess groups being studied. These were defined as the top decile and top quartiles of daily mileage travelled and daily emissions generated. These groups are henceforth referred to as M10 (top decile of mileage), M25 (top quartile of mileage), E10 (top decile of emissions generated), and E25 (top quartile of emissions generated). The rationale for the definition of two excess thresholds was to further compare very top users against a more general excess user group in addition to comparing them to the general overall population.

A comprehensive analysis of the descriptive statistics pertaining to the previously defined excess groups and the overall population was conducted. The main aim of this process was to gain initial insights into how the specific characteristics being studied might impact travel behaviour. Additionally, this process aimed to determine whether there were any substantial disparities among the different excess groups or trip datasets being studied that could be statistically significant. Furthermore, detailed breakdowns of the contributions made by each trip purpose towards the total travel and emissions generated by the average user of each excess group and the average person was carried out. The comparison of these breakdowns aimed to uncover potential factors driving the differing travel behaviours exhibited by the various excess groups. These steps aimed not only to provide a preliminary overview of the data being studied, but also to provide a foundation for deeper exploration into the relationships between the characteristics being studied and the travel behaviour of the respective user groups.

To better understand the relationships between the characteristics being studied and the travel behaviour of the German populace, BLR models were developed. This method models the dependent variable as a logit of P, the probability that the dependent variable takes a value of 1, given the values of the independent variables, which can be categorical or continuous. The use of a logit model allows for easy interpretation of the model results through the derivation of odds ratios. The general model is provided in Equation (2) below.

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k \qquad (2)$$

where,

$P(Y=1)$: Probability that dependent variable Y = 1 given X (e.g. being a member of an excess group)

b_0 : Intercept

$X_1, X_2, \dots, X_k$: Independent variables

$b_1, b_2, \dots, b_k$: Coefficients associated with the independent variables

The coefficients obtained from the models were then converted to the odds ratio through calculating the exponential of the respective coefficients. This eased the interpretation of the model results as it quantified the change in odds directly when examining changes in the independent variables.

All statistical analyses in this thesis performed using RStudio, with the BLR process accomplished using the glm() function. The final model structures were selected based on their Akaike Information Criterion values. This was carried out through the application of the stepAIC() function in the MASS package.

In the context of this thesis, the binary dependent variable was defined as whether a person was a member of a certain excess group, with their presence in said excess group taking a value of 1. This resulted in a total of eight models due to there being four excess groups in each of the two datasets. Doing so allowed for the comparison of the results of the different models to evaluate the relationships between the characteristics studied and the travel behaviour of the survey respondents more comprehensively.

3.4. EV ownership analysis

Supplementing the observations of variables significant in affecting EV adoption from literature, a statistical analysis analogous to that described earlier was carried out on the car ownership data obtained from the vehicles and households datasets of MiD2017. In the place of excess groups defined in the above section, households that owned EVs were examined. As the car ownership was household based, certain variables that were person-based such as gender and age could not be investigated in this thesis when looking at EV adoption based on MiD2017. The variables considered in each statistical analysis is provided in Table 6 below.

Table 6: Variable application in analyses

Variable	Excess group analysis	EV ownership analysis
Personal level variables		
Gender	X	-
Age group	X	-
Employment status	X	X
Secondary residence	X	-
Level of education	X	X
Household level variables		
Region type	X	X
Home ownership status	X	X
Household car ownership	X	X
Household motorbike ownership	X	X
Household bike ownership	X	X
Weighted household size	X	X
Economic status of household	X	X
Household with minors	X	X
Highest car segment in household	X	X
Household EV ownership	X	-

3.5. Emissions accounting

As mentioned previously in Chapter 2, the differences in parameter definition between studies could result in large variations in the emission factor values calculated by the different LCA studies. Consequently, careful consideration was taken when deciding on the emission factor values to be applied in this thesis. Considering the tendency for emission factor values to decrease over time due to factors such as technological advances, only LCAs studying the four years before and after 2017 were selected when considering values to use for evaluating the emissions generated by the dataset populations. This was done to ensure that values used were more accurate to the year that MiD2017 was carried out.

For the projection of EV adoption effects on emissions, the year 2030 was selected as the studies reviewed unanimously use it as a future prediction date. The emissions factors calculated by the selected studies are shown in Figure 2 below, with the same article numbers defined in Chapter 2. From these, the mean emission factor value for vehicles of each fuel type was calculated for the years 2017 and 2030 respectively. The final values for each fuel type and year are shown in Table 7 below.

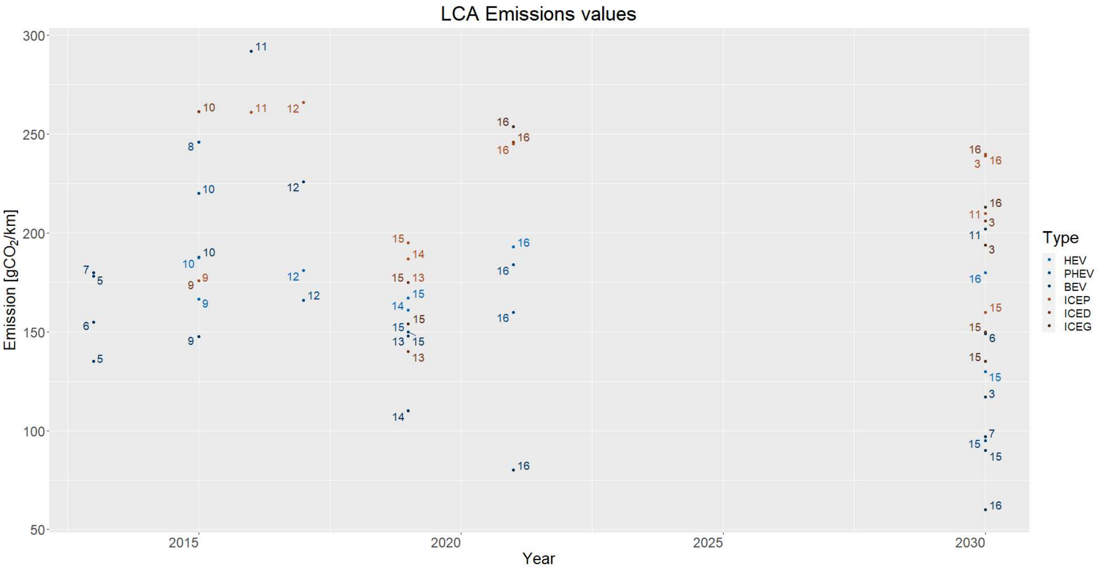

Figure 2: LCA values of selected studies

Table 7: Mean emission factors for each fuel type and year

Fuel type	Lifetime emissions in 2017 [g/km]	Lifetime emissions in 2030 [g/km]
ICEP	214.971	212.25
ICED	199.626	198.667
ICEG	204.000	180.667
HEV	181.831	135.000
BEV	165.798	119.167
ICEP	214.971	212.25

4. Statistical analysis

4.1. Excess groups in all trips

Descriptive statistics of the overall population, referred to as OV, and that of excess groups were compiled to provide initial insights into the relationship between the characteristics studied and travel behaviour. Table 8 lists the descriptive statistics of the characteristics studied in this thesis for all trips.

Table 8: Descriptive statistics of all trips

Variable	OV [%] N = 121,426	M10 [%] N = 12,143	M25 [%] N = 30,356	E10 [%] N = 12,143	E25 [%] N = 30,356
Gender					
Male	51.7	60.4	57.5	62.9	58.1
Female	48.3	39.6	42.5	37.1	42.0
Age					
0-17	11.8	8.5	7.3	3.0	3.0
18-24	4.0	4.1	4.7	4.5	4.8
25-59	47.3	57.1	58.4	64.2	63.2
60 and above	37.0	30.3	29.6	28.3	29.1
Employment status					
Full-time employed	35.0	49.5	47.9	58.2	53.7
Part-time employed, 18-34 hours per week	13.3	10.9	13.3	11.2	14.1
Marginally employed, 11-17 hours per week	1.3	1.0	1.1	0.9	1.1
Part-time job/Internship	0.7	0.5	0.7	0.6	0.7
Employed (unspecified)	0.0*	0.1	0.1	0.1	0.1
Apprenticeship	1.2	1.1	1.4	1.2	1.4
Not working	48.5	37.0	35.6	27.9	29.1
Secondary residence					
Yes	4.5	7.4	5.8	7.5	5.7
No	95.5	92.6	94.2	92.5	94.3
Level of education					
No degree (yet)	12.0	8.6	7.6	3.3	3.3
Elementary or secondary school	15.5	10.3	11.6	9.8	11.9
Secondary school leaving certificate	25.7	22.3	25.1	23.8	26.8
Technical college entrance qualification, Abitur	15.0	16.6	17.1	18.4	18.2
College or university degree	29.9	40.6	37.0	43.0	38.1
Other degree	1.8	1.6	1.7	1.7	1.7
Region type					
Urban	64.2	63.7	62.9	62.7	63.1
Rural	35.8	36.3	37.1	37.3	36.9
Home ownership status					
Renting	25.1	27.0	25.1	27.5	25.8
Homeowning	74.9	73.0	74.9	72.6	74.2
Household car ownership					
<1	49.4	45.0	43.4	36.3	37.2
1+	50.6	55.0	56.6	63.7	62.8
Household motorbike ownership					
<1	95.8	95.0	94.8	94.2	94.2
1+	4.2	5.0	5.3	5.8	5.8
Household bike ownership					
<1	20.4	16.9	17.4	18.0	18.1
1+	79.6	83.1	82.6	82.0	81.9
Household driving licence ownership					
<1	22.7	20.9	20.7	15.6	16.8
1+	77.3	79.1	79.3	84.4	83.2
Weighted household size					
1 person	11.3	10.8	10.8	14.2	13.6
Up to 1.5 persons	43.8	43.2	42.2	42.7	42.8
Less than 2 persons	6.5	7.3	7.0	6.6	6.2
2+ persons	38.4	38.7	39.9	36.5	37.4

Economic status of household					
Very low	2.4	1.9	2.0	1.8	1.9
Low	7.8	5.1	6.3	4.8	6.0
Medium	39.6	33.8	34.8	33.5	34.9
High	39.9	44.4	44.1	45.5	44.5
Very high	10.4	14.9	12.8	14.5	12.7
Household with minors					
All adult household	67.5	67.2	67.0	72.2	71.7
Minor in household	32.5	32.8	33.0	27.8	28.4
Highest car segment in household					
Small	9.8	7.8	8.4	8.8	9.3
Compact	31.5	28.7	29.6	29.5	30.0
Medium	42.1	44.3	43.7	42.2	42.2
Large	16.7	19.3	18.4	19.5	18.6
Household EV ownership					
No EV in household	98.7	98.7	98.6	99.0	98.7
EV in household	1.3	1.3	1.4	1.0	1.3

* denotes non-zero values

As seen in Table 8, the same patterns were observed for all four excess groups compared to the overall population for most of the variables studied. Compared to the overall population, the following attributes were more prevalent in the excess groups:

- Male
- Working age (18-59 years of age in the context of this study)
- Employed full-time
- Have a secondary residence
- Possess a secondary school leaving certificate or higher
- Live in a rural region
- Rent their homes
- Higher household car, motorbike, and bike ownership
- Greater household driving licence possession
- Larger household sizes for excess mileage groups, smaller household sizes for excess emissions groups
- Higher household economic status
- Live in households with minors for excess mileage groups, live in households without minors for excess emissions groups
- Own larger cars

Most of the observed patterns listed above were consistent with that mentioned in existing literature. When considering the effect of household sizes, studies that considered this variable arrived at differing conclusions, with Wadud et al. (2022) claiming that single adult households were more likely to be excess emitters but not excess travellers while Buchs and Schnepf (2013) observed larger households to be more likely to emit in excess. Additionally, existing studies conclude that households containing children were more likely to be excess emitters, however the opposite was observed in this analysis. The pattern observed in these two variables in this analysis could be a result of the smaller households or those without minors generally having lower occupancy rates in the trips they make.

The complete results of the logistic regression models for all trips are provided in Appendix A (Tables 17-20). The patterns observed from the models for all trips were largely consistent with those observed in the descriptive statistics. The patterns observed for the person-level variables (gender, age group, employment status, secondary residence, level of education) were all consistent with those in the descriptive statistics. The sole exception to this was the M10 group, where minors were found to be most likely to be excess travellers. This could be due to the interaction of this variable with the other variables studied. Of note from the personal variables is women being consistently at least 20% less likely than men to be excess users as well as those with a technical college entrance qualification or Abitur and higher being consistently at least 30% more likely to be excess users than those who either do not or do not yet have any qualifications, which were well cited in existing studies.

While some variables were in some cases insignificant in the effect on excess travel and excess emissions, the household-level variables studied presented generally similar patterns to that observed in the descriptive statistics. Persons living in rural regions were found to be around 10% more likely than those living in urban regions to be excess users, which is in line with existing studies. The only variable where results differed from the descriptive statistics was the influence that having minors in the household had. While households with minors were more prevalent in excess traveller groups and less prevalent in excess emitter groups, the models found households with minors significantly more likely both excess travellers and excess emitters, but only for the M25 and E25 groups. Household car licence ownership was only found to be significant in the E10 group, this could be due to increased mobility options present due to the household having more available drivers. EV ownership was also only significant in the E10 group, with EV-owning households 26% less likely to be excess emitters.

Initial models completed presented a negative relation between household economic status and the likelihood of being an excess user. This was contrary to existing studies and statistics, which generally find that mileage travelled increases with income (Bureau of Transportation Statistics, 2012; Department for Transport, 2023). After further examination it was discovered that the interaction of this variable with another, annual household car mileage per person, was the cause. Consequently, this variable was removed from the final list variables being studied.

4.2. Excess groups in daily trips

Table 9 lists the descriptive statistics of the characteristics studied in this thesis for daily trips.

Table 9: Descriptive statistics of daily trips

Variable	OV [%] N = 118,265	M10 [%] N = 11,826	M25 [%] N = 29,466	E10 [%] N = 11,826	E25 [%] N = 29,466
Gender					
Male	51.5	59.8	56.6	62.3	57.2
Female	48.5	40.2	43.4	37.7	42.9
Age					
0-17	11.8	6.0	6.5	0.5	1.5
18-24	4.0	4.8	4.9	5.0	5.0
25-59	47.3	60.3	59.3	68.6	64.3
60 and above	37.0	28.9	29.4	25.9	29.2
Employment status					
Full-time employed	34.9	51.5	48.2	61.5	53.8
Part-time employed, 18-34 hours per week	13.4	12.6	14.1	13.1	15.4
Marginally employed, 11-17 hours per week	1.3	0.9	1.1	1.0	1.1
Part-time job/Internship	0.7	0.6	0.7	0.6	0.7
Employed (unspecified)	0.0*	0.1	0.0	0.1	0.0*
Apprenticeship	1.2	1.5	1.5	1.5	1.5
Not working	48.6	32.8	34.4	22.3	27.4
Secondary residence					
Yes	4.4	5.5	4.9	5.4	4.8
No	95.6	94.5	95.1	94.6	95.2
Level of education					
No degree (yet)	12.0	6.2	6.7	0.9	1.8
Elementary or secondary school	15.6	11.3	12.4	10.9	12.8
Secondary school leaving certificate	25.9	24.7	26.4	25.9	28.5
Technical college entrance qualification, Abitur	15.0	17.4	17.4	19.8	18.5
College or university degree	29.7	38.7	35.4	40.9	36.6
Other degree	1.8	1.7	1.7	1.7	1.8
Region type					
Urban	64.1	60.2	62.0	60.6	62.2
Rural	35.9	39.8	38.0	39.4	37.9
Home ownership status					
Renting	25.1	25.0	24.4	25.6	25.1
Homeowning	75.0	75.0	75.6	74.4	74.9
Household car ownership					
<1	49.4	41.6	42.3	32.9	35.7
1+	50.6	58.4	57.7	67.1	64.3
Household motorbike ownership					
<1	95.8	94.3	94.7	93.8	94.1
1+	4.2	5.8	5.3	6.2	5.9
Household bike ownership					
<1	20.5	17.4	18.0	17.9	18.7
1+	79.5	82.6	82.0	82.1	81.3
Household driving licence ownership					
<1	22.7	20.2	20.3	15.6	16.2
1+	77.3	79.8	79.7	84.5	83.8
Weighted household size					
1 person	11.4	11.0	11.0	14.9	14.1
Up to 1.5 persons	43.7	42.2	42.0	41.4	42.8
Less than 2 persons	6.4	6.7	6.7	5.9	5.8
2+ persons	38.5	40.2	40.3	37.8	37.3
Economic status of household					
Very low	2.4	2.0	2.0	1.8	1.9
Low	7.9	5.5	6.7	6.1	6.6
Medium	39.7	34.2	35.5	33.2	35.5
High	39.8	44.8	43.8	45.4	44.1
Very high	10.3	13.4	12.0	13.5	11.9
Household with minors					
All adult household	67.5	67.3	67.5	72.4	72.5
Minor in household	32.5	32.8	32.6	27.6	27.5

Highest car segment in household					
Small	9.9	8.1	8.6	9.4	9.7
Compact	31.5	29.5	29.9	29.8	30.3
Medium	42.0	43.1	43.2	41.9	41.6
Large	16.6	19.4	18.3	18.9	18.5
Household EV ownership					
No EV in household	98.7	98.6	98.6	98.9	98.7
EV in household	1.3	1.4	1.5	1.2	1.3

* denotes non-zero values

As seen in Table 9, the same patterns were observed across the board for the daily trips dataset compared to those observed in the all trips dataset. The sole exception to this was the influencing of home ownership. Persons from homeowning were found to be more prevalent in excess mileage groups, as compared to persons from renting households in both excess mileage and excess emissions groups in the all trips dataset.

Looking at the logistic regression models for daily trips in Appendix A (Tables 21-24), the patterns observed for the personal-level variables were the same. The exception to this is the secondary residence status, which was found to be insignificant in all daily trips models. This suggests that individuals with a secondary residence made more than their proportional share of long-distance trips (100km).

Examining the household level variables, the region type in which the users lived was found to be insignificant in every model except for that of the E25 group. This suggested a more balanced split between urban and rural residents in the excess groups when only excluding long-distance trips. Persons from households renting their homes were seen to be more likely to be excess users in the all trips dataset. In contrast, persons from homeowning households were found to be likely to be excess users when excluding long-distance trips. In this dataset, while household driving licence ownership was found to be insignificant in influencing excess travel, it was found to be significant in influencing excess emissions, with an individual from a household possessing more driving licences being around 10% more likely to emit in excess. This suggests that households with higher driving licence possession may have lower occupancy per trip. Finally, household EV ownership was only found to be significant in influencing the likelihood of being excess emitters.

4.3. Trip purpose analysis

To better understand the possible factors behind the varying travel behaviour of the various excess groups, the proportions of the total mileage and emissions generated by the average person in both the overall population and each excess group for each trip purpose was examined. The respective proportions of mileage and emissions by trip purpose are provided in Tables 10 and 11 below.

Table 10: Proportions of mileage by trip purpose

Proportions of mileage		Total value [km]	Commuting [%]	Business [%]	Maintenance [%]	Leisure [%]	Accompaniment [%]
All trips	OV	49.05	21.0	8.0	23.6	40.3	7.1
	M10	240.80	15.1	12.1	16.6	50.0	6.2
	M25	139.77	19.6	10.0	19.2	44.4	6.7
	E10	222.5	20.5	13.7	16.9	43.8	5.2
	E25	133.95	22.7	10.7	19.3	41.2	6.0
Daily trips	OV	34.03	25.4	6.1	28.1	32.3	8.0
	M10	121.33	24.0	10.7	21.9	35.2	8.2
	M25	84.49	26.6	8.2	23.8	33.5	7.9
	E10	108.29	35.3	12.9	21.6	24.0	6.2
	E25	78.96	32.0	9.1	24.2	27.7	7.0

Table 11: Proportions of emissions by trip purpose

Proportions of emissions		Total value [kg]	Commuting [%]	Business [%]	Maintenance [%]	Leisure [%]	Accompaniment [%]
All trips	OV	6.74	27.6	10.2	24.9	31.6	5.6
	M10	29.57	20.0	17.1	17.6	40.2	5.1
	M25	18.35	26.3	13.4	20.1	34.8	5.4
	E10	31.50	26.0	17.4	17.7	34.7	4.2
	E25	19.06	29.4	13.4	20.3	32.1	4.8
Daily trips	OV	5.06	32.4	7.5	28.4	25.5	6.2
	M10	17.35	31.8	13.6	21.3	26.9	6.4
	M25	12.41	34.6	10.1	23.3	25.8	6.1
	E10	19.25	40.1	13.8	20.7	20.6	4.7
	E25	13.10	38.2	10.3	23.6	22.6	5.3

Looking at Tables 10 and 11, the patterns observed when examining the proportions or mileage and proportions of emissions for each trip purpose were generally similar. It was universally observed that business trips made up a larger proportion of excess users' mileage and emissions while maintenance and accompaniment trips made up a smaller proportion of excess users' mileage and emissions. Commuting travel also generally made up less of excess users' travel and emissions compared to the average person when considering all trips, with the opposite observed for daily trips. These observations suggest that business trips are a significant contributor to excess travel overall while commuting trips only significantly contribute to excess travel and emissions in daily trips.

When looking at the role of leisure trips, it was observed that these trips generally contributed to a larger proportion of excess users' mileage and emissions compared to the average person, with the exception being excess emitters when considering daily trips. This implies that leisure travel is a significant factor in excess travel but only significantly contributes to excess emissions in long-distance trips.

When comparing the two datasets (all trips compared to daily trips) against each other, it was observed that business and leisure made up a larger proportion of the total mileage and emissions in all trips while commuting, maintenance and accompaniment made up a larger proportion of the total mileage and emissions in daily trips. This reflects the nature of business and leisure trips and provides further reason to examine two datasets instead of just all trips.

The proportions of total emissions that each trip purpose makes up were also compared to that of total mileage. It was observed that commuting and business travel resulted in a greater proportion of emissions than they did for mileage. The inverse was observed for leisure and accompaniment trips. The most probable reason for this was the occupancy for these trips, which was confirmed through the calculation of the average occupancy for each trip purpose, which are provided in Table 12 below.

Table 12: Average occupancy rates for each trip purpose and dataset

Trip purpose	Commuting	Business	Maintenance	Leisure	Accompaniment
All trips	1.33	1.28	1.55	2.14	2.20
Daily trips	1.32	1.27	1.54	2.12	2.19

4.4. EV adoption

Descriptive statistics of the overall population and that of EV-owning households were also compiled to provide insights into the relationships between the characteristics studied and EV adoption behaviour, this is shown in Table 13 below. The effects of personal characteristics on EV adoption could not be examined from MiD2017 data due to the recording of car ownership based on households rather than persons in the survey. As this analysis only analyses household car ownership without any relation to trips made, it was decided to not limit the households analysed in this study to just those included in the previous analysis. Hence, a total of 127,869 households were examined in this analysis, with 1,455 of them owning at least one EV.

Table 13: Descriptive statistics of car ownership

Variable	OV [%] N = 127,869	EV [%] N = 1,455
Highest employment status		
Full-time employed	20.3	20.3
Part-time employed, 18-34 hours per week	9.0	11.3
Marginally employed, 11-17 hours per week	1.2	0.8
Part-time job/Internship	0.7	0.6
Employed (unspecified)	0.0	0.0*
Apprenticeship	1.4	1.6
Not working	67.4	65.4
Highest level of education		
No degree (yet)	0.5	0.6
Elementary or secondary school	13.5	7.4
Secondary school leaving certificate	25.6	18.7
Technical college entrance qualification, Abitur	16.9	16.4
College or university degree	40.7	54.3
Other degree	2.9	2.6
Region type		
Urban	66.4	67.4
Rural	33.6	32.6
Home ownership status		
Renting	29.0	23.3
Homeowning	71.0	76.7
Household car ownership		
<1	47.0	43.1
1+	53.0	56.9
Household motorbike ownership		
<1	95.5	95.1
1+	4.5	4.9
Household bike ownership		
<1	22.6	21.1
1+	77.4	78.9
Household driving licence ownership		
<1	17.1	16.2
1+	82.9	83.8
Weighted household size		
1 person	18.4	12.4
Up to 1.5 persons	49.1	51.6
Less than 2 persons	4.9	4.7
2+ persons	27.7	31.3
Economic status of household		
Very low	2.8	1.5
Low	8.2	4.7
Medium	43.9	35.5
High	35.5	42.3
Very high	9.7	16.0
Household with minors		
All adult household	78.0	76.8
Minor in household	22.0	23.2
Highest car segment in household		
Small	13.0	14.5
Compact	33.5	44.4
Medium	37.5	29.8
Large	16.0	11.3

* denotes non-zero values

Compared to the overall population, the following attributes were more prevalent in the excess groups:

- At least one member who was full-time or part-time
- At least one member who was highly educated
- Larger household size
- Higher household car and motorbike ownership
- Lower household bike ownership
- Higher household driving licence ownership
- Households with minors
- Higher household economic status
- Homeowning households
- Live in an urban region
- Own smaller cars

The above observations were largely consistent with that of the studies examined in the literature review. It was noted that a larger than expected proportion of households recorded a highest employment status of 'Not working', and this was further investigated through the inclusion of weighting factors, but this ultimately proved to not significantly change the percentage of households not working. Therefore, weighting factors were ultimately not used in this analysis.

The logistic regression results of EV adoption are provided in Table 14 below. As seen in Table 14, homeowning households were 33% more likely to adopt EVs than households that rented their homes while households with higher car ownership were 55% more likely to adopt EVs. Additionally, it was observed that single person households were the least likely to adopt EVs, with other households at least 44% more likely to adopt EVs. The economic status of households was also found to be significant in affecting EV adoption likelihood, with the highest category 2.5 times as likely to adopt EVs compared to the lowest. Households with minors were also 19% more likely than those without to adopt EVs. The above observations were all consistent with that of the reviewed literature.

While employment status and region type were deemed to be significant in affecting EV ownership in existing studies, they were found to be insignificant in this model. A higher level of education was seen to positively influence EV adoption, which is also consistent with the reviewed literature. However, households with no qualifications were found to be most likely to adopt EVs, which is contrary to observations from literature. This could be a result of the small sample size in this analysis. this could be a result of the small sample size in this model as only 1.2% of car owning households in MiD2017 owned EVs. Moreover, ownership levels of bikes, both motorised and non-motorised, as well as driving licences were found to be insignificant in affecting EV adoption likelihood. Households that owned smaller cars were also found to be more likely to own EVs, with EV ownership likelihood decreasing with increasing car size owned by a household.

Table 14: Logistic regression results of EV adoption

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	-5.12	0.01	-12.59	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	-0.87	0.42	-2.47	0.013	*
Secondary school leaving certificate	-0.67	0.51	-1.96	0.050	.
Technical college entrance qualification, Abitur	-0.44	0.65	-1.27	0.204	
College or university degree	-0.17	0.84	-0.50	0.618	
Other degree	-0.46	0.63	-1.23	0.217	
Home ownership status					
Renting	(Reference)				
Homeowning	0.28	1.33	4.33	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.44	1.55	6.85	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	0.75	2.12	7.94	0.000	***
Less than 2 persons	0.37	1.44	2.13	0.033	*
2+ persons	0.74	2.10	6.62	0.000	***
Economic status of household					
Very low	(Reference)				
Low	0.05	1.06	0.22	0.825	
Medium	0.32	1.38	1.48	0.140	
High	0.58	1.78	2.62	0.009	**
Very high	0.93	2.55	4.09	0.000	***
Household with minors					
All adult household	(Reference)				
Minor in household	0.17	1.19	1.75	0.081	.
Highest car segment in household					
Small	(Reference)				
Compact	-0.14	0.87	-1.67	0.096	.
Medium	-0.89	0.41	-9.70	0.000	***
Large	-1.18	0.31	-10.43	0.000	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

4.5. Comparison of excess groups and EV adoption

Having a comprehensive picture of factors that are significant in affecting travel behaviour as well as those significant in affecting EV adoption, a comparison of the general characteristics pointing to excess travel behaviour against characteristics pointing to increased EV adoption was carried out. An overview of this comparison is provided in Table 15 below.

Table 15: Overview of travel behaviour and EV adoption effects

Variable	**Excess mileage**	**Excess emissions**	**EV adoption**
	Personal level variables		
Gender	Male		
Age group	Working age		Inconclusive
Employment status	Full-time employed		
Secondary residence	All trips: Yes		NA
Level of education	Higher		
	Household level variables		
Region type	All trips: Rural Daily trips: Insignificant	Rural	Inconclusive
Home ownership status	All trips: Renting Daily trips: Homeowning		Homeowning
Household car ownership	More		
Household motorbike ownership	More		Insignificant
Household bike ownership	More		Insignificant
Household driving licence ownership	Insignificant	More	Insignificant
Weighted household size	Larger	Smaller	Larger
Economic status of household	Higher		
Household with minors	Minor in HH		
Highest car segment in household	Larger		Smaller

While the statistical analysis carried out in this thesis could not examine the effects of personal-level attributes on EV adoption, existing literature nonetheless have provided some insight how some of the personal level variables interact with EV adoption likelihood. As seen in Table 15 above, there were various variables that were observed to have similar characteristics that point to increased excess mileage, excess emissions, as well as EV adoption. Hence, focusing on these groups would be able to provide maximal effect when encouraging and implementing a transition to EVs. These groups include:

- Males
- Individuals of working age
- Full-time employed individuals
- Highly educated individuals
- Households with high car ownership
- Households with higher economic status
- Households with minors

Additionally, homeowning households should be prioritised as they are significant in increasing the likelihood of both excess travel for daily trips and EV adoption. However, improving charging infrastructure for EVs could lead to households that rent their home also adopting EVs for their long-distance travel. Additionally, the difference in car segment characteristics point to a need to cater to the demands of households that purchase larger vehicles when pushing a transition from ICEVs to EVs. Only through acknowledging these similarities and differences between the influences that the various characteristics have on excess travel and EV adoption can an effective reduction in emissions be achieved.

5. Effects of EV adoption

To evaluate the potential effects that the transition to EVs in Germany may have on emission levels, several hypothetical scenarios were defined. To highlight the potential emissions reductions that can be achieved by targeting different groups, five possible EV adoption scenarios were defined for the year 2030.

Firstly, a base scenario (2030Base) that assumed no change in fleet composition, meaning no changes to the adoption rates of EVs compared to that in MiD2017, was defined. This scenario was defined to highlight the potential emissions reductions arising solely from technological advances and changes in electricity carbon intensity. One scenario each was then defined with the assumption of households that contained members that were part of either the top decile or quartile groups adopted EVs for all their trips in 2030, referred to as 2030T10 and 2030T25 respectively. These scenarios were defined with the intention of highlighting the potentially significant impacts that the adoption of EVs by excess users would have on emissions reductions, as they contribute to more than their fair share of emissions.

Furthermore, a scenario (2030HH) assuming all households that were likely to adopt EVs did so was defined. These households were selected based on the results of the previous section. Since information on the highest employment status and education were available from the statistical analysis, these were included in the definition of this scenario. Consequently, households included in this selection of households likely to adopt EVs must have had all the following attributes:

- Higher car ownership
- Higher economic status
- Had minors

Additionally, the selected households had either one of the following attributes:

- Contained a member who is highly educated
- Contained a member who is at least employed part-time

Finally, a scenario (2030All) that assumed every household adopted to EVs was defined. The projected emission values are calculated on a per person basis and are provided in Table 16 below.

Table 16: Scenarios and projected emissions values

Scenario	Change in fleet composition	Value [kg/day]	Percentage reduction compared to 2017 [%]
2017	None	6.74	-
2030Base	None	6.65	1.3
2030T10	Top 10% households all adopt EVs	5.28	21.7
2030T25	Top 25% households all adopt EVs	4.66	30.9
2030HH	Likely adopters all adopt EVs	4.32	35.9
2030All	All users adopt EVs	4.11	39.0m

As seen in Table 16, assuming no change in fleet composition, a decrease of only 1.3% in emissions compared to 2017 would be achieved by 2030. This illustrates how the role of technological advancements and the decline in the carbon intensity of electricity to achieve emissions reductions is very limited, highlighting a definite need to transition from ICEVs to EVs. In contrast, the adoption of EVs by the top 10% and top 25% of users would generate reductions more than their proportions of the population. Therefore, it is vital to target these groups to maximise the reduction of emissions between now and 2050 when the passenger car fleet is expected to be fully electric.

The adoption of EVs by all likely adopters, while reducing a significant portion of emissions compared to current levels, also encompasses many households. Hence, the excess groups should be targeted first before these likely adopters if the goal is to rapidly cut down on emissions generated from passenger car use. Lastly, if a complete transition to EVs is realised, a reduction of 39% of emissions is expected. This underscores how the adoption of EVs does not eliminate emissions resulting from passenger car use but rather only helps to minimise it. Therefore, steps such as reducing the carbon intensity of electricity and reducing emissions generated from vehicle life phases such as manufacture need to be taken to ensure that sustainability goals for the passenger car fleet can be met.

6. Further discussion and conclusion

6.1. Limitations

One limitation of this thesis when considering the potential reduction in carbon emissions was that several assumptions regarding the population studied were made. No changes in the population size, vehicle ownership nor travel behaviour were assumed in this study, which does not hold true. For example, the daily distance travelled by the average German has increased from 33 to 39 kilometres from 2002 to 2017. Meanwhile the mode share of passenger cars in terms of total kilometres travelled has decreased from 80% to 75% over the same period (Nobis & Kuhnimhof, 2018). While changes in travel behaviour over time do indeed occur, the inclusion of the previous version of MiD, carried out in 2002, was not done due to the time between this study and the time that this survey was carried out. Moreover, the study was carried out in a time when EVs had no significant presence in the German fleet.

The emission factors used in this thesis also have a fundamental effect on the results of the respective analyses. Hence, the accuracy of the results obtained from this study is limited by the LCA studies used, although careful consideration with regards to the studies referenced was done. Finally, the EV adoption projection carried out in this thesis carried many assumptions and simplifications due to the scope of this thesis. However, it nonetheless provides insight into the contributions that targeting the identified groups in this thesis could have on emissions reduction efforts.

6.2. Recommendations for further works

This thesis analyses the data from MiD2017 to draw its conclusions, the methods used in this thesis could be applied in the near future to the upcoming version of MiD, MiD2022. This would be able to provide a more up to date and accurate picture of the travel behaviour as well as the EV adoption patterns of the German populace. Additionally, comparison of the two surveys could yield insights into when transitioning to EVs alone can reduce emissions in the face of possible increases in car ownership, in contrast to the Singaporean government's policy of a vehicle growth rate of zero as a means of combating climate change (Ministry of Transport, 2023).

This thesis did not consider changes in population and travel behaviour, nor did it comprehensively predict or model the adoption of EVs. Therefore, the application of more extensive methods such as using agent-based simulations to model market diffusion that account for such changes should be used. This would yield more practical and accurate results and provide answers as to the true potential for emissions reductions from the process of transitioning towards EVs.

6.3. Conclusion

The transition of passenger car fleets from ICEVs towards EVs is a hot topic that is gaining more attention in recent years with efforts from various stakeholders such as governments to encourage this shift. This thesis sought to examine similarities and differences between the effects of different characteristics on travel behaviour and EV adoption. This was achieved through the statistical analysis of data from MiD2017 and comparison of the effects of the respective characteristics. Males, those employed full-time and those of higher education, as well as households that owned more cars, households with higher economic status and had children were consistently found to be related to increased travel and emissions as well as increased likelihood of EV adoption.

The findings from these analyses were further incorporated into scenarios to project the possible reductions in emissions resulting from the adoption of EVs by the various identified groups. This highlighted the importance of targeting specific groups such as the top 10% of travellers and emitters when trying to reduce emissions through the transition of the passenger car fleet to EVs.

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Declaration of independent work

I hereby confirm that this thesis was written independently by myself without the use of any sources and resources beyond those cited, and all passages and ideas taken from other sources are cited accordingly. This thesis has not previously been submitted elsewhere for purposes of assessment.

Munich, 2023.10.31

John Leong Jia Jun

Appendices

Appendix A: BLR model results

Table 17: Logistic regression results of top travelling decile (M10) for all trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	-2.05	0.13	-19.48	0.000	***
Gender					
Male	(Reference)				
Female	-0.24	0.79	-10.47	0.000	***
Age					
0-17	(Reference)				
18-24	-0.26	0.77	-1.84	0.066	.
25-59	-0.21	0.81	-1.44	0.150	
60+	-0.28	0.75	-1.99	0.046	*
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.41	0.66	-11.17	0.000	***
Marginally employed, 11-17 hours/week	-0.41	0.66	-3.97	0.000	***
Part-time job/Internship	-0.41	0.67	-2.94	0.003	**
Employed (unspecified)	0.36	1.43	0.93	0.353	
Apprenticeship	-0.43	0.65	-3.76	0.000	***
Not working	-0.36	0.69	-10.76	0.000	***
Secondary residence					
Yes	(Reference)				
No	-0.53	0.59	-13.05	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.15	1.16	1.02	0.308	
Secondary school leaving certificate	0.36	1.43	2.53	0.011	*
Technical college entrance qualification, Abitur	0.56	1.75	3.92	0.000	***
College or university degree	0.71	2.02	4.95	0.000	***
Other degree	0.39	1.47	2.39	0.017	*
Region type					
Urban	(Reference)				
Rural	0.09	1.10	4.31	0.000	***
Home ownership status					
Renting	(Reference)				
Homeowning	-0.15	0.86	-6.21	0.000	***
Household bike ownership					
<1	(Reference)				
1+	0.14	1.15	5.13	0.000	***
Economic status of household					
Very low	(Reference)				
Low	-0.25	0.78	-2.84	0.004	**
Medium	0.02	1.02	0.31	0.760	
High	0.13	1.14	1.67	0.095	.
Very high	0.30	1.36	3.78	0.000	***
Highest car segment in household					
Small	(Reference)				
Compact	0.11	1.12	2.69	0.007	**
Medium	0.23	1.25	5.53	0.000	***
Large	0.28	1.32	6.14	0.000	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 18: Logistic regression results for top travelling quartile (M25) for all trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	-1.42	0.24	-19.09	0.000	***
Gender					
Male	(Reference)				
Female	-0.23	0.80	-14.66	0.000	***
Age					
0-17	(Reference)				
18-24	0.39	1.47	4.43	0.000	***
25-59	0.28	1.33	3.14	0.002	**
60+	0.08	1.08	0.87	0.383	
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.31	0.73	-13.04	0.000	***
Marginally employed, 11-17 hours/week	-0.51	0.60	-7.65	0.000	***
Part-time job/Internship	-0.36	0.69	-4.18	0.000	***
Employed (unspecified)	-0.24	0.78	-0.76	0.447	
Apprenticeship	-0.19	0.83	-2.75	0.006	**
Not working	-0.46	0.63	-20.08	0.000	***
Secondary residence					
Yes	(Reference)				
No	-0.32	0.72	-10.31	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	-0.03	0.97	-0.29	0.770	
Secondary school leaving certificate	0.15	1.16	1.64	0.100	
Technical college entrance qualification, Abitur	0.28	1.33	3.20	0.001	**
College or university degree	0.40	1.49	4.46	0.000	***
Other degree	0.21	1.24	2.08	0.037	*
Region type					
Urban	(Reference)				
Rural	0.13	1.14	8.95	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.17	1.19	9.89	0.000	***
Household motorbike ownership					
<1	(Reference)				
1+	0.11	1.12	3.42	0.001	***
Household bike ownership					
<1	(Reference)				
1+	0.12	1.13	6.65	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	0.15	1.17	5.97	0.000	***
Less than 2 persons	0.05	1.05	1.17	0.243	
2+ persons	0.04	1.04	1.24	0.213	
Economic status of household					
Very low	(Reference)				
Low	-0.07	0.93	-1.35	0.176	
Medium	-0.01	0.99	-0.16	0.875	
High	0.05	1.05	1.05	0.295	
Very high	0.13	1.14	2.48	0.013	*
Household with minors					
All adult household	(Reference)				
Minor in household	0.15	1.16	5.57	0.000	***
Highest car segment in household					
Small	(Reference)				
Compact	0.06	1.06	2.01	0.044	*
Medium	0.12	1.12	4.18	0.000	***
Large	0.14	1.15	4.57	0.000	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 19: Logistic regression results of top emitting decile (E10) for all trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	-2.42	0.09	-21.84	0.000	***
Gender					
Male	(Reference)				
Female	-0.36	0.69	-16.45	0.000	***
Age					
0-17	(Reference)				
18-24	0.88	2.42	5.99	0.000	***
25-59	0.92	2.50	6.08	0.000	***
60+	0.75	2.11	4.92	0.000	***
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.46	0.63	-13.50	0.000	***
Marginally employed, 11-17 hours/week	-0.63	0.53	-6.18	0.000	***
Part-time job/Internship	-0.47	0.63	-3.71	0.000	***
Employed (unspecified)	0.08	1.08	0.20	0.842	
Apprenticeship	-0.39	0.68	-3.91	0.000	***
Not working	-0.67	0.51	-20.95	0.000	***
Secondary residence					
Yes	(Reference)				
No	-0.50	0.61	-12.81	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	-0.22	0.81	-1.46	0.143	
Secondary school leaving certificate	0.04	1.04	0.24	0.808	
Technical college entrance qualification, Abitur	0.27	1.31	1.85	0.064	.
College or university degree	0.39	1.48	2.71	0.007	**
Other degree	0.11	1.12	0.68	0.497	
Region type					
Urban	(Reference)				
Rural	0.15	1.17	7.39	0.000	***
Home ownership status					
Renting	(Reference)				
Homeowning	-0.08	0.92	-3.26	0.001	**
Household car ownership					
<1	(Reference)				
1+	0.28	1.33	11.00	0.000	***
Household bike ownership					
<1	(Reference)				
1+	0.07	1.07	2.53	0.011	*
Household driving licence ownership					
<1	(Reference)				
1+	0.08	1.08	2.24	0.025	*
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	-0.05	0.95	-1.46	0.145	
Less than 2 persons	-0.10	0.91	-1.92	0.055	.
2+ persons	-0.10	0.90	-2.65	0.008	**
Economic status of household					
Very low	(Reference)				
Low	-0.25	0.78	-3.04	0.002	**
Medium	-0.05	0.95	-0.70	0.483	
High	0.02	1.02	0.33	0.741	
Very high	0.12	1.12	1.50	0.135	
Highest car segment in household					
Small	(Reference)				
Compact	0.02	1.02	0.57	0.566	
Medium	0.07	1.07	1.76	0.079	.
Large	0.11	1.12	2.67	0.008	**
Household EV ownership					
No EV in household	(Reference)				
EV in household	-0.30	0.74	-3.17	0.002	**

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 20: Logistic regression results of top emitting quartile (E25) for all trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	-1.82	0.16	-29.33	0.000	***
Gender					
Male	(Reference)				
Female	-0.27	0.77	-17.22	0.000	***
Age					
0-17	(Reference)				
18-24	1.02	2.77	10.55	0.000	***
25-59	0.93	2.54	9.40	0.000	***
60+	0.72	2.06	7.24	0.000	***
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.33	0.72	-14.63	0.000	***
Marginally employed, 11-17 hours/week	-0.61	0.54	-9.59	0.000	***
Part-time job/Internship	-0.42	0.66	-5.06	0.000	***
Employed (unspecified)	-0.41	0.66	-1.31	0.191	
Apprenticeship	-0.38	0.69	-5.53	0.000	***
Not working	-0.76	0.47	-34.59	0.000	***
Secondary residence					
Yes	(Reference)				
No	-0.24	0.79	-7.44	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.07	1.07	0.67	0.500	
Secondary school leaving certificate	0.26	1.30	2.77	0.006	**
Technical college entrance qualification, Abitur	0.39	1.48	4.13	0.000	***
College or university degree	0.46	1.59	4.84	0.000	***
Other degree	0.26	1.29	2.39	0.017	*
Region type					
Urban	(Reference)				
Rural	0.09	1.09	6.10	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.41	1.50	24.21	0.000	***
Household motorbike ownership					
<1	(Reference)				
1+	0.11	1.11	3.43	0.001	***
Household bike ownership					
<1	(Reference)				
1+	0.10	1.10	5.50	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	0.01	1.01	0.32	0.749	
Less than 2 persons	-0.15	0.86	-3.62	0.000	***
2+ persons	-0.09	0.91	-3.19	0.001	**
Household with minors					
All adult household	(Reference)				
Minor in household	0.09	1.09	3.39	0.001	***
Highest car segment in household					
Small	(Reference)				
Compact	0.02	1.02	0.75	0.453	
Medium	0.07	1.07	2.67	0.007	**
Large	0.10	1.10	3.29	0.001	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 21: Logistic regression results of top travelling decile (M10) for daily trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	0.15	1.16	2.37	0.018	*
Gender					
Male	(Reference)				
Female	-0.13	0.87	-9.27	0.000	***
Age					
0-17	(Reference)				
18-24	0.63	1.87	8.14	0.000	***
25-59	0.42	1.52	5.26	0.000	***
60+	0.21	1.24	2.66	0.008	**
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.16	0.85	-6.69	0.000	***
Marginally employed, 11-17 hours/week	-0.29	0.75	-4.84	0.000	***
Part-time job/Internship	-0.38	0.68	-4.62	0.000	***
Employed (unspecified)	-0.10	0.91	-0.28	0.778	
Apprenticeship	-0.10	0.90	-1.30	0.195	
Not working	-0.52	0.59	-22.67	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.25	1.29	3.21	0.001	**
Secondary school leaving certificate	0.32	1.38	4.18	0.000	***
Technical college entrance qualification, Abitur	0.34	1.41	4.42	0.000	***
College or university degree	0.33	1.40	4.30	0.000	***
Other degree	0.31	1.36	3.37	0.001	***
Home ownership status					
Renting	(Reference)				
Homeowning	0.09	1.10	5.56	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.34	1.40	19.86	0.000	***
Household motorbike ownership					
<1	(Reference)				
1+	0.13	1.14	3.46	0.001	***
Household bike ownership					
<1	(Reference)				
1+	0.11	1.11	6.32	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	0.15	1.16	5.77	0.000	***
Less than 2 persons	-0.02	0.98	-0.59	0.552	
2+ persons	0.04	1.04	1.28	0.200	
Economic status of household					
Very low	(Reference)				
Low	0.12	1.12	2.52	0.012	*
Medium	0.09	1.09	2.07	0.038	*
High	0.07	1.08	1.73	0.084	.
Very high	0.05	1.05	1.08	0.280	
Household with minors					
All adult household	(Reference)				
Minor in household	0.19	1.21	7.01	0.000	***
Highest car segment in household					
Small	(Reference)				
Compact	0.04	1.04	1.57	0.116	
Medium	0.10	1.10	3.95	0.000	***
Large	0.10	1.10	3.37	0.001	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 22: Logistic regression results of top travelling quartile (M25) for daily trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	1.53	4.60	14.87	0.000	***
Gender					
Male	(Reference)				
Female	-0.11	0.89	-4.71	0.000	***
Age					
0-17	(Reference)				
18-24	0.58	1.79	4.63	0.000	***
25-59	0.55	1.73	4.20	0.000	***
60+	0.33	1.39	2.50	0.012	*
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.13	0.88	-2.79	0.005	**
Marginally employed, 11-17 hours/week	-0.22	0.81	-1.91	0.056	.
Part-time job/Internship	-0.49	0.61	-3.52	0.000	***
Employed (unspecified)	-0.26	0.77	-0.43	0.666	
Apprenticeship	0.00	1.00	0.03	0.979	
Not working	-0.45	0.64	-10.66	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.20	1.22	1.54	0.123	
Secondary school leaving certificate	0.36	1.43	2.83	0.005	**
Technical college entrance qualification, Abitur	0.42	1.52	3.31	0.001	***
College or university degree	0.38	1.46	2.97	0.003	**
Other degree	0.36	1.43	2.35	0.019	*
Household car ownership					
<1	(Reference)				
1+	0.36	1.43	11.99	0.000	***
Household bike ownership					
<1	(Reference)				
1+	0.16	1.18	5.74	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	0.24	1.27	5.22	0.000	***
Less than 2 persons	0.04	1.04	0.52	0.606	
2+ persons	0.10	1.10	1.76	0.078	.
Economic status of household					
Very low	(Reference)				
Low	0.15	1.17	2.10	0.036	*
Medium	0.16	1.17	2.43	0.015	*
High	0.19	1.20	2.76	0.006	**
Very high	0.11	1.12	1.46	0.144	
Household with minors					
All adult household	(Reference)				
Minor in household	0.13	1.14	2.51	0.012	*
Highest car segment in household					
Small	(Reference)				
Compact	0.05	1.05	1.21	0.226	
Medium	0.11	1.12	2.70	0.007	**
Large	0.15	1.16	2.95	0.003	**

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 23: Logistic regression results of top emitting decile (E10) for daily trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	0.18	1.20	2.80	0.005	**
Gender					
Male	(Reference)				
Female	-0.19	0.82	-12.50	0.000	***
Age					
0-17	(Reference)				
18-24	1.07	2.92	13.89	0.000	***
25-59	0.99	2.70	12.40	0.000	***
60+	0.84	2.32	10.35	0.000	***
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.16	0.85	-5.89	0.000	***
Marginally employed, 11-17 hours/week	-0.26	0.77	-3.95	0.000	***
Part-time job/Internship	-0.48	0.62	-5.51	0.000	***
Employed (unspecified)	-0.35	0.70	-1.01	0.313	
Apprenticeship	-0.11	0.89	-1.36	0.172	
Not working	-0.63	0.53	-25.14	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.21	1.23	2.61	0.009	**
Secondary school leaving certificate	0.32	1.37	4.05	0.000	***
Technical college entrance qualification, Abitur	0.32	1.38	4.09	0.000	***
College or university degree	0.26	1.30	3.32	0.001	***
Other degree	0.32	1.38	3.40	0.001	***
Home ownership status					
Renting	(Reference)				
Homeowning	0.08	1.09	4.78	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.48	1.62	26.10	0.000	***
Household motorbike ownership					
<1	(Reference)				
1+	0.14	1.15	3.37	0.001	***
Household bike ownership					
<1	(Reference)				
1+	0.07	1.07	3.69	0.000	***
Household driving licence ownership					
<1	(Reference)				
1+	0.11	1.11	4.63	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	-0.12	0.89	-4.16	0.000	***
Less than 2 persons	-0.37	0.69	-8.01	0.000	***
2+ persons	-0.30	0.74	-8.70	0.000	***
Economic status of household					
Very low	(Reference)				
Low	0.11	1.11	2.19	0.028	*
Medium	0.08	1.09	1.90	0.057	.
High	0.07	1.07	1.45	0.146	
Very high	0.00	1.00	-0.04	0.965	
Household with minors					
All adult household	(Reference)				
Minor in household	0.13	1.14	4.23	0.000	***
Household EV ownership					
No EV in household	(Reference)				
EV in household	-0.17	0.84	-2.73	0.006	**

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Table 24: Logistic regression results of top emitting quartile (E25) for daily trips

Term	Coefficient	Odds Ratio	Z	p-value	Significance
(Intercept)	0.69	1.99	8.62	0.000	***
Gender					
Male	(Reference)				
Female	-0.19	0.83	-10.51	0.000	***
Age					
0-17	(Reference)				
18-24	0.98	2.65	10.92	0.000	***
25-59	0.98	2.66	10.59	0.000	***
60+	0.82	2.27	8.70	0.000	***
Employment status					
Full-time employed	(Reference)				
Part-time employed, 18-34 hours/week	-0.12	0.89	-3.49	0.000	***
Marginally employed, 11-17 hours/week	-0.15	0.86	-1.84	0.066	.
Part-time job/Internship	-0.47	0.62	-4.46	0.000	***
Employed (unspecified)	-0.46	0.63	-1.10	0.271	
Apprenticeship	-0.08	0.92	-0.83	0.408	
Not working	-0.58	0.56	-18.33	0.000	***
Level of education					
No degree (yet)	(Reference)				
Elementary or secondary school	0.20	1.22	2.21	0.027	*
Secondary school leaving certificate	0.33	1.38	3.63	0.000	***
Technical college entrance qualification, Abitur	0.33	1.39	3.67	0.000	***
College or university degree	0.30	1.35	3.28	0.001	**
Other degree	0.40	1.50	3.58	0.000	***
Region type					
Urban	(Reference)				
Rural	0.04	1.04	2.10	0.036	*
Home ownership status					
Renting	(Reference)				
Homeowning	0.09	1.10	4.35	0.000	***
Household car ownership					
<1	(Reference)				
1+	0.52	1.68	22.29	0.000	***
Household motorbike ownership					
<1	(Reference)				
1+	0.13	1.14	2.50	0.013	*
Household bike ownership					
<1	(Reference)				
1+	0.08	1.09	3.83	0.000	***
Household driving licence ownership					
<1	(Reference)				
1+	0.14	1.15	4.99	0.000	***
Weighted household size					
1 person	(Reference)				
Up to 1.5 persons	-0.09	0.91	-2.36	0.019	*
Less than 2 persons	-0.41	0.66	-7.29	0.000	***
2+ persons	-0.30	0.74	-6.66	0.000	***
Economic status of household					
Very low	(Reference)				
Low	0.16	1.17	2.77	0.006	**
Medium	0.16	1.17	3.08	0.002	**
High	0.14	1.15	2.67	0.008	**
Very high	0.08	1.09	1.48	0.140	
Household with minors					
All adult household	(Reference)				
Minor in household	0.12	1.13	3.11	0.002	**
Highest car segment in household					
Small	(Reference)				
Compact	-0.02	0.98	-0.71	0.477	
Medium	0.01	1.01	0.40	0.687	
Large	0.09	1.09	2.24	0.025	*
Household EV ownership					
No EV in household	(Reference)				
EV in household	-0.26	0.77	-3.57	0.000	***

Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1